Storypoint Problem Exploration - talenddataquality

September 6, 2024

1 Storypoint Prediction: Problem Exploration

1.1 Problem Statement

In modern agile development settings, software is developed through repeated cycles (iterative) and in smaller parts at a time (incremental), allowing for adaptation to changing requirements at any point during a project's life. A project has a number of iterations (e.g. sprints in Scrum). Each iteration requires the completion of a number of user stories, which are a common way for agile teams to express user requirements.

There is thus a need to focus on estimating the effort of completing a single user story at a time rather than the entire project. In fact, it has now become a common practice for agile teams to go through each user story and estimate its "size". Story points are commonly used as a unit of measure for specifying the overall size of a user story.

1.2 Problem Formulation

Input: A string of length N that contains a story's name and description $C = \{c_1, c_2, c_3, ..., c_n\}$. For each story, a set of text embeddings that contains features $E = \{e_1, e_2, e_3, ..., e_m\}$ extracted from C has been provided.

Output: A natural number P associated with the story point of that user story

1.3 Dataset Information

Text Embeddings: Text embeddings are a way to convert words or phrases from text into a list of numbers, where each number captures a part of the text's meaning. The dataset has been preprocessed and converted into two kinds of text embeddings. You can choose to work with either of them or both: - Doc2Vec: Input strings are transformed into fixed-length vectors of size 128. These vectors capture the semantic meaning of words and their relationships within a document. - Look-upTable: Input strings are transformed into fixed-length vectors of size 2264. These vectors are obtained via transforming each word in the input strings into an identifier number, then padded to the length of the longest sample.

Dataset Structure & Format: Storypoint Estimation Dataset is stored in 3 folders labeled *raw data*, *look-up*, and *doc2vec*. Within each folder are 3 CSV files for training, testing, validation. Each csv file has the following columns: - `issuekey` : The unique identifier for a story. - `storypoint`: The correct number of storypoint. - An embedding column (`embedding` or `doc2vec`) contains text embedding vectors. The raw data csv will not have this and instead contain two columns with story `name` and `description`.

1.4 Exploration

1.4.1 Raw data exploration

[ ]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.feature_extraction.text import CountVectorizer
```

Output exploration

[ ]:
```python
# Import raw data from the CSV file

project_name = 'talenddataquality'

all_data = pd.concat([pd.read_csv('data/' + project_name + '/' + project_name +␣
↪'_train.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
↪'_valid.csv'),
                      pd.read_csv('data/' + project_name + '/' + project_name +␣
↪'_test.csv')])

print('Check the shape of the dataset', all_data.shape)
```

```
Check the shape of the dataset (1136, 4)
```

[ ]:
```python
all_data.drop(['issuekey'], axis=1, inplace=True)
all_data.head()
```

[ ]:
```
                                               title  \
0  sql server single sign support doesnt work dat…
1                 remove two columns frequency tables
2               connection analysis informationschema
3    multiple analysis indicators grayed cannot used
4  view invalid rows menu display table analysis …

                                         description  storypoint
0  data profiler perspective cant use single sign…           3
1  bcolumnbasicjrxml report frequency tables must…           8
2  create connection analysis mysql retrieve info…           5
3  attempting analyze table columns analysis indi…           3
4  rule join condition impossible view invalid ro…           8
```

First, let take a look at the distribution of the story point:

Interpretation of Skewness Values:

- **Skewness > 0**: Right-skewed distribution.
- **Skewness < 0**: Left-skewed distribution.

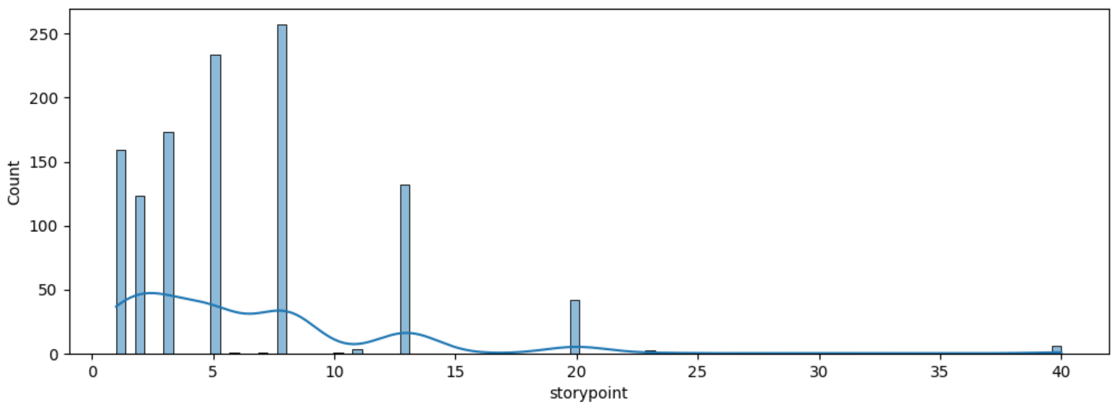
- **Skewness = 0**: Symmetrical distribution (like a normal distribution).

Interpretaion of kurtosis: - **Leptokurtic (Kurtosis > 3)**: The distribution has heavier tails and a sharper peak than the normal distribution. Data points are more likely to produce extreme values. The distribution has a higher peak and fatter tails. - **Platykurtic (Kurtosis < 3)**: The distribution has lighter tails and a flatter peak than the normal distribution. Data are fewer extreme values compared to a normal distribution. - **Mesokurtic (Kurtosis 3)**: The distribution has a similar kurtosis to the normal distribution, indicating a moderate level of outliers.

[ ]:
```
# Draw a histogram of the story points
plt.figure(figsize=(12, 4))
plt.xticks(np.arange(0, max(all_data['storypoint']) + 1, 5))
sns.histplot(all_data['storypoint'], bins=100, kde=True)

print('Skewness:', all_data['storypoint'].skew())
print('Kurtosis:', all_data['storypoint'].kurt())
```

```
Skewness: 2.1933435430999726
Kurtosis: 8.526189136065922
```



[ ]:
```
tmp = pd.concat([all_data['storypoint'].value_counts(),
                 all_data['storypoint'].value_counts() / all_data.shape[0] *␣
 ↪100],
                axis=1, keys=['Counts', 'Percentage (%)'])
tmp.head(20)
```

[ ]:

	Counts	Percentage (%)
storypoint		
8	257	22.623239
5	234	20.598592
3	173	15.228873
1	159	13.996479
13	132	11.619718
2	123	10.827465

20	42	3.697183
40	6	0.528169
11	3	0.264085
23	2	0.176056
28	1	0.088028
6	1	0.088028
7	1	0.088028
10	1	0.088028
24	1	0.088028

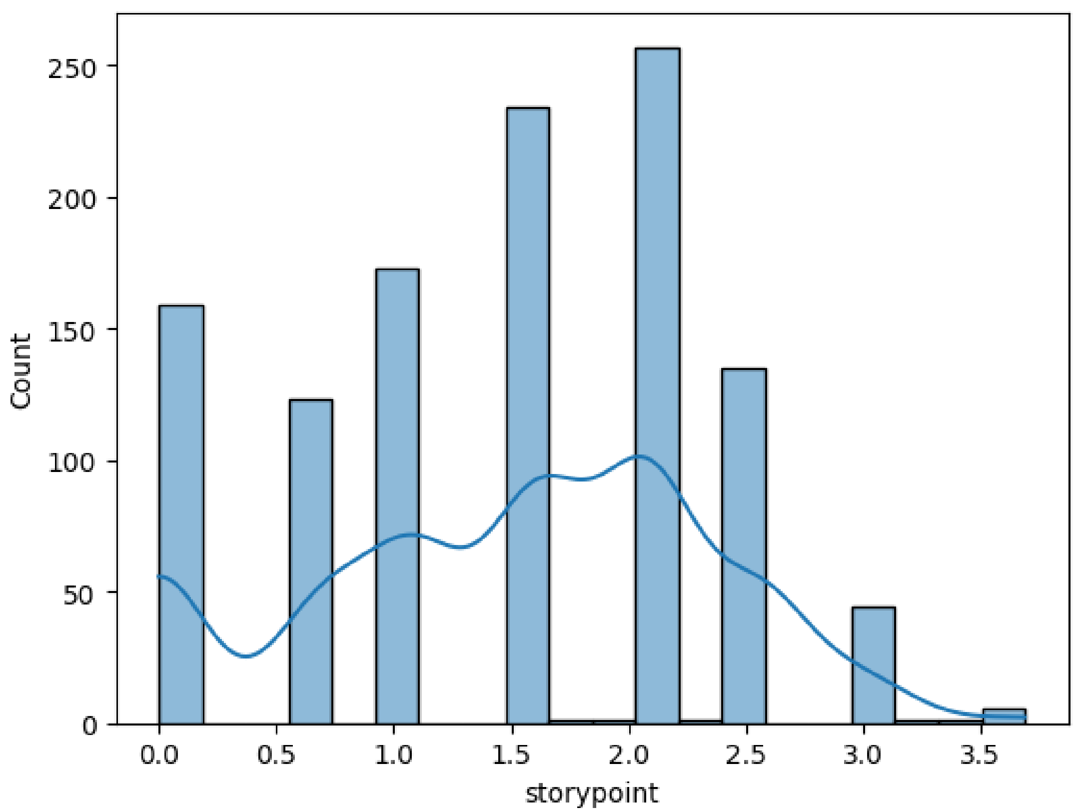
At the first sight, this data is bad. Then take a look at the statistic values, this data is even worse. Its distribution of the label is **right-skewed** and **leptokurtis**. This means if we use this to train model, the right side of the data can be the outliers and make the models become unsuable.

I will try 2 solutions: - Use log-scale on the label - Remove all the examples with label greater than a threshold (20, 30 or 40)

The first solution: logarithm magic

[ ]:
```
sns.histplot(np.log(all_data['storypoint']), bins=20, kde=True)
```

[ ]:
```
<Axes: xlabel='storypoint', ylabel='Count'>
```



```
[ ]: print('Skewness:', np.log(all_data['storypoint']).skew())
     print('Kurtosis:', np.log(all_data['storypoint']).kurt())
```

```
Skewness: -0.22847624477809397
Kurtosis: -0.6888346728821104
```

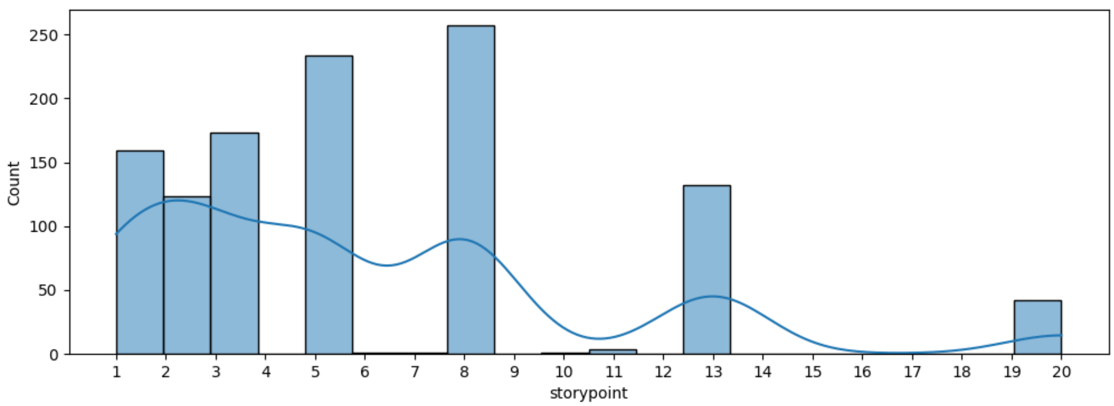
The kurtotis is negative now but still near 3 than before. The skewness is near zero which is a good sign

The second solution: Dismantle and Cleave

```
[ ]: threshold = 20 # This threshold means that we will take all the examples with␣
      ↪story points less than or equal to 20

     new_data = all_data[all_data['storypoint'] <= threshold]
     plt.figure(figsize=(12, 4))
     plt.xticks(np.arange(0, max(new_data['storypoint']) + 1, 1))
     sns.histplot(new_data['storypoint'], bins=threshold, kde=True)
     print('Fitered percentage: ', round(1 - new_data.shape[0] / all_data.shape[0],␣
      ↪2) * 100, '%')
```

```
Fitered percentage:  1.0 %
```



Input exploration The input of this problem is 2 texts: title and description. First we will find some statistics:

```
[ ]: title_lengths = all_data['title'].apply(lambda x: len(x.split(' ')))
     print('Title analysis:')
     print('    - Mean length:', round(title_lengths.mean()))
     print('    - Min length:', title_lengths.min())
     print('    - Max length:', title_lengths.max())

     description_lengths = all_data['description'].apply(lambda x: len(x.split(' '))␣
      ↪if type(x) != float else 0)
```

```python
print('Description analysis:')
print('    - Mean length:', round(description_lengths.mean()))
print('    - Min length:', description_lengths.min())
print('    - Max length:', description_lengths.max())
```

```
Title analysis:
   - Mean length: 7
   - Min length: 1
   - Max length: 19
Description analysis:
   - Mean length: 38
   - Min length: 0
   - Max length: 1070
```

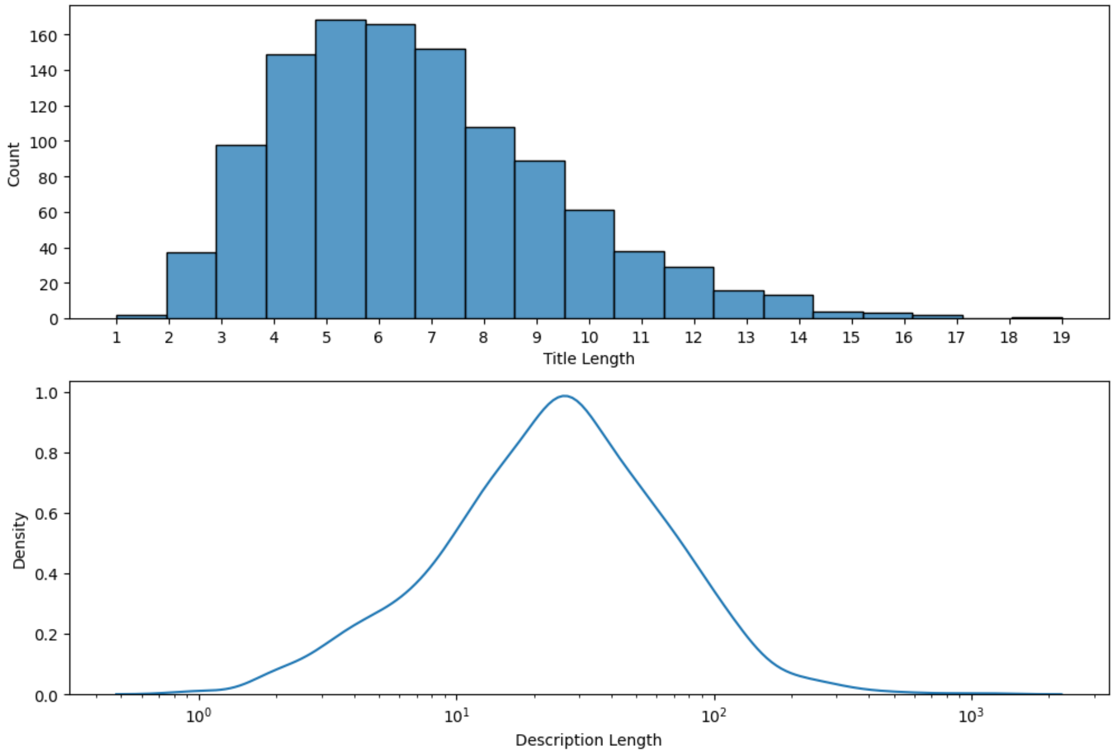
Plot the histogram of the title length and KDE of the description length (exclude 0):

[ ]:
```python
plt.figure(figsize=(12, 8))

plt.subplot(2, 1, 1)
plt.xticks(np.arange(0, max(title_lengths) + 1, 1))
plt.xlabel('Title Length')
sns.histplot(title_lengths, bins=max(title_lengths))

plt.subplot(2, 1, 2)
plt.xlabel('Description Length')
plt.xscale('log')
sns.kdeplot(description_lengths[description_lengths > 0])
```

[ ]:
```
<Axes: xlabel='Description Length', ylabel='Density'>
```



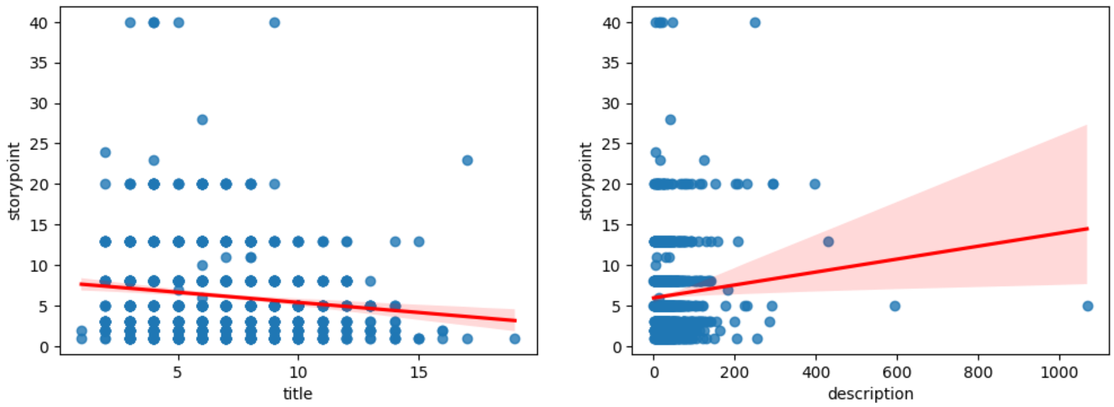
I think we should check the correlation between title length and description length:

[ ]:
```
plt.figure(figsize=(12, 4))

plt.subplot(1, 2, 1)
plt.xticks(np.arange(0, max(all_data['title'].apply(lambda x: len(x.split('␣
↪')))) + 1, 5))
sns.regplot(x=all_data['title'].apply(lambda x : len(x.split(' '))),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})

plt.subplot(1, 2, 2)
sns.regplot(x=all_data['description'].apply(lambda x : len(x.split(' ')) if␣
↪type(x) != float else 0),
            y=all_data['storypoint'],
            line_kws={'color': 'red'})
```

[ ]:
```
<Axes: xlabel='description', ylabel='storypoint'>
```



The title has a significant corelation with the storypoint. The description show a big slope line but with a big deviation. I think these 2 features still help model traning somehow

Let dive deeper in the input:

Title analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data['title'])

dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()), columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(10)
```

```
(1535, 2)
```

[ ]:

	word	frequency
704	zos	1534
835	zip	1533
1018	zero	1532
683	yet	1531
1182	yes	1530
788	year	1529
309	xsd	1528
69	xmxm	1527
739	xml	1526
244	wrong	1525

Description analysis:

[ ]:
```
count_vectorizer = CountVectorizer()
count_vectorizer.fit(all_data[all_data['description'].isnull() == False]['description'])
```

```
dictionary = pd.DataFrame(list(count_vectorizer.vocabulary_.items()),␣
 ↪columns=['word', 'frequency'])
dictionary.sort_values(by='frequency', ascending=False, inplace=True)
print(dictionary.shape)
dictionary.head(20)
```

```
(6303, 2)
```

[ ]:

	word	frequency
5971	zshen	6302
2194	zos	6301
3990	zones	6300
3999	zone	6299
6029	zipcode	6298
640	zip	6297
4348	zhaos	6296
4324	zhao	6295
4573	zeroresultsthe	6294
4752	zero	6293
3426	youre	6292
3992	york	6291
4346	yinyueyantalendbj	6290
4344	yin	6289
3823	yields	6288
2964	yet	6287
2185	yes	6286
2944	yellow	6285
5581	yearto	6284
2877	years	6283

Yet I don't find any thing special about the words in input except so many things are bad.

1.4.2 Solving strategies

My first intuitation in this problem is that the hard part is not on the algorithm we use, it is on the **embedding** part. Therefore, in case the given embedded datasets work not properly, I will use a better embedding method which is **Bidirectional Encoder Representations from Transformers (BERT)**. Also, I will try an old way to embedding the text too: **Bag of words**.

In conclusion, I will have 4 ways to embed the text: - doc2vec (already available) - Look up (already available) - Bag Of Words - BERT

About algorithm, I will try all the regression algorithm that may give a good result:

- Ridge Regressor
- Support Vector Regressor
- Random Forest Regressor
- Gradient Boosting
- XGBoost

- Lightgbm
- Blended

Maybe, we can change the problem to the classification problem with 100 labels (desparation confirmed). In the classification problem, I will use: - Support Vector Classifier - Softmax Regression (Multinomial Logistic Regression) - Random Forest - Adaboost - XGBoost

Thanks to the libaries, the implementation of all the algorithm shrinks to its minimum form.

At last, there is still a situation that all of mentioned model don't give a good result. This gamble is thrilling (hopeless).

"But would you lose?"

Nah, I'd win.